Developing a Methodology to Improve the Allocation of Specialized Health Resources for Acutely Injured Persons

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Introduction. Inappropriate triage following acute injury may result in misallocation of specialized health resources, increased health care costs, reduced or delayed access to care, and increased death and disability. Although triage criteria have been developed, they vary widely, and inappropriate triage rates are high (50% - 85%). The purpose of this project was to evaluate the ability of decision tree induction to predict need for specialized trauma resources in acutely injured persons. We considered any person who was admitted to the trauma center's ICU or died prior to being admitted to the ICU as needing specialized trauma resources.

Modeling Technique. Unlike neural nets, decision tree induction produces human-readable classification models. This is important for at least three reasons: (1) the availability of computing resources in emergency settings limits the utility of triage models that require a computer to perform complex analyses, (2) understandable rules will increase initial acceptance because current triage methodology uses human-readable lists, and (3) learned rules will encourage and direct more basic research into the physiologic reasons behind the rules. If the rules are not understandable to humans, such questions are difficult to explore. The decision tree induction algorithm we used was C4.5.[1]

Data. All patients experiencing a brain injury (Abbreviated Injury Score of 2-5 for the head region) admitted to a Level 1 Trauma Center in the Southeastern United States between January 1, 1999 and December 31, 2001 were included in the sample (*N*=2831). All subjects were victims of blunt force trauma. Twenty-eight retrospective variables were extracted from the trauma registry for each subject. Three additional variables were derived from the retrospective data. For clinical decision support to be useful to emergency clinicians, it must be a byproduct of their workflow (not an additional step). Therefore to measure the utility of emergency clinical decision support, models should be developed based on what is known at various points in the process. To test this, variables were divided into three groups (prehospital, referring hospital, and trauma center) that reflected information available at that level of care.

Experimental Methodology. To test how well C4.5 can learn a model from the given data using each of these three variable sets, we used 10-fold cross-validation in which each data set is partitioned into ten random, equal-sized subsets. For each subset, an experiment is run in which the subset is used to test the accuracy of a model that is learned using the other nine subsets as training data. This method has been shown to provide a good estimate of model accuracy.[2]

Results. Table 1 summarizes the results our experiments.

	accuracy	sens	spec
prehosp	74.3	.636	.836
ref hosp	76.2	.668	.843
trauma cent	80.3	.765	.835

Table 1. Summary of results. (*sens* is sensitivity, and *spec* is specificity.)

Accuracy is how well model predicts need for specialized resources. A lower sensitivity reflects a greater rate of undertriage. A lower specificity reflects a greater rate of overtriage.

Discussion. Decision tree induction with C4.5 demonstrated good accuracy in predicting need for specialized health resources following injury. Information gathered at higher levels of care (downstream) improved accuracy of prediction. Although limitations are associated with using retrospective data, the use of decision tree (and rule) induction has great potential to improve specialized health care resource allocation resulting in improved quality of life and decreased death and disability following injury. Furthermore, it will foster additional research in several ways including: (1) identifying information available 'downstream' that may be moved 'upstream' to improve health care resource allocation, (2) identifying which predictor variables are amenable to clinical intervention, (3) identifying what data should be collected that is not currently being collected, and (4) identifying complex biological relationships worthy of basic science research.

References.

1. Quinlan, JR. *C4.5: Programs for Machine Learning*. Morgan Kaufmann. 1993.

2. Kohavi, R. "A study of cross-validation and bootstrap for accuracy estimation and model selection." In *Proceedings of the Fourteenth IJCAI*. 1995.